A HYBRID MODEL BASED AND STATISTICAL FAULT DIAGNOSIS SYSTEM FOR INDUSTRIAL PROCESS

A Thesis

by

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ABSTRACT

This thesis presents a hybrid model based and statistical fault diagnosis system, which applied on the nonlinear three-tank model. The purpose of fault diagnosis is generating and analyzing the residual to find out the fault occurrence. This fault diagnosis system includes residual generator and residual processor. The fault generator is applied with the Luenberger observer, which has its own algorithm to compute the parameters. The residual processor is applied with the Shiryayev sequential probability ratio test, which calculating the posteriori probabilities to detect and isolate a change in residual in the independent measurement.

The thesis starts with introduction and literature review, and then shows the methods of residual generation and residual processing. The chapter six presents the simulation results, which operated by MATLAB Simulink. The fault diagnosis system successfully captured different kind of fault in three-tank model. The results prove the effectiveness of this fault diagnosis system.

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CHAPTER I

INTRODUCTION

Modern life depends increasingly on technological system service and product all the time. In many areas, such as power grids, communication system, transportation system, and factory production line are now highly automated. But there still remain some manual activity, which operated by manpower for very important tasks in process plant. These tasks are about indicating the abnormal events and isolating an abnormal event timely, taking an appropriate decision, and bringing the process back to normal status.

However, due to system complexity and broad diversity of the diagnostic action, which includes a variety of malfunctions. These malfunctions include parameter drifts, unit failure and degradation. It increases difficulty to reliance on human operator to deal with the broad scope of abnormal or emergencies events. In addition, the diagnosis task usually emphasizes a quick detection, and it gains difficulty because the measurements in the process may often be inadequate and incomplete due to various reasons such as sensor bias or actuator failure.

Form the difficult condition be mentioned is previous paragraph, there is no surprise that facility operators have possible to take wrong actions and lead the abnormal situation even worse. And thus, the incorrect decisions tend to have significant safety and environmental problem and issue. It is very common that minor accidents such as daily sensor bias cause a major catastrophe; while the factory failures are infrequently lead to a factory disaster, which resulting in occupational injuries, system crashes, and economic cost.

The fault detection and diagnosis system is very crucial in modern industry for abnormal event management. A variety of computer-aided approaches and mathematical techniques are developed over decades. It makes the modern control system are becoming more and more sophisticated so that the control system should be highly reliable and secure. An effective way to ensure the control system performance and safety is to detect the sensor, actuator, and component failures. So scientists developed different kind of diagnosis tools to discover the failure and correct the abnormal behavior. They lead the fault diagnosis techniques have ability to solve the different kinds of process faults and difficulties in real time solution.

In the past, computers replaced human operators to do an automated regulatory control. This has created a great research in system steady performance and process efficiency. The current topic is how the intelligent control system provides human operators assistance timely, safely, and efficiently. Scientists view this goal as a next breakpoint in control system diagnosis research.

We hope the system failure will not occur; however, this objective is obviously unattainable. That is, faults are always be concerned. With the increasing complexity of engineering system, the demands of reliability are rising. In non-automated systems, human operates the fault detection function; while in automated systems this function is performed automatically. It is useful to design a powerful fault detection method to improve system reliability.

There are two kinds of fault detection approaches. One is the hardware redundancy, which is a very common method. It uses multiple identical sensors with voting scheme to compare the outputs directly. Usually, for detect the fault and identify the faulty sensor, the system needs three identical sensors are required if one of sensor is fail. The hardware redundancy need a little computation and very straightforward. But this method is expensive and it has other inconvenient ways such as weight and space.

The other methodology is the analytical redundancy, which applies software, mathematical and signal processing technique. There is a model to compare the expected system behavior with observed system behavior. The observed system is constructed by computer software technique, and it runs in parallel to the expected system. It is reasonable that the observed system will follow the same behavior with the expected system because it is driven by the same input. Apparently, when expected has a fault, a faulty signal will be produced in observed system.

From the above two paragraphs, we can understand that hardware redundancy would impractical in some situation, and analytical redundancy will has limitation due to robustness and software problem. That is why we invented the analytical redundancy management, which can diagnose the change of system stochastic properties in most situations. The ability for analyzing an abruptly change is critical for system robustness and fault tolerant system. In analytical redundancy method, with the aid of the systematic decision rule is an important role for analyzing the residual signal or providing a sufficient numerical statistics, and it is widely studied in online fault detection and identification field.

The core idea about model-based fault detection and isolation technique is using model of system to generate the information about fault. The quality of the model is essential for fault detection system, and for elimination of false alarm. The behavior between model inputs and outputs has been utilized in the fault diagnosis system design.

Furthermore, when expected system and observed system differ significantly, we presume the fault has occurred. This signal represents the difference between expected and observed system variables are called the residual, which can be used to detect and identify faults. Usually, the residual is zero during fault-free status, and nonzero at other times. When the residual is not zero, a fault signal would be announced and it is necessary to identify the faulty component. These procedures need much more computation than hardware redundancy, and it does not require any redundant sensor.

The fault detection and diagnosis technique have been studied in many researches and applications to enhance the reliability and performance of the target systems. Residual generation and residual evaluation compose a fault diagnosis system. The system includes observer and decision-making mechanism. The observer-based fault detection and diagnosis technique is widely used for residual generation.

Different fault detection approach needs different models. In control system design and analysis, a useful model has to show its state space relationship and input-output behavior in a simple way. For this reason, the model would be simplified or linearized so that the model might ignore the some physical features and only keep the attributes which relevant to system design.

The model for designing the fault detection and isolation has to think about robustness, and not be affected by unknown inputs and model uncertainty. The result of robustness depends on several factors, such as the number of detected fault, unknown inputs, model uncertainty, system parameter and measured variables. Hence, to find out input, output, or other measurement has a possible source of fault is the first procedure for determining the reduced model.

In some case, the residual signal is not zero in a fault-free status. It caused by disturbance, noise, and other model uncertainty. Therefore, to avoid the false alarm and also ensure a successful fault detection task, a strategy is needed. The purpose of the strategy is that faults can be separated from disturbance and noises, which both of these are called unknown inputs. The residual evaluation is devised for this purpose. In this method, the residual is under evaluated and compare with a threshold. When the value of residual signal is higher than threshold, a fault decision is made. Setting an appropriate threshold is an important task. Higher threshold causes missed detection that implies that a set of fault hide in the system. On the other hand, the lower threshold results a false alarm. The false alarm means the system declared an alarm, but there is no fault in real system. For this reason, the threshold usually is viewed as a fault tolerant policy and compromising the unknown inputs is a crucial part in fault detection and diagnosis technique.

Because of disturbance, noise and uncertainties, the residual, which generated by an observer fails to go to zero during fault-free status. It would be difficult to capture the fault occurrence only by simple threshold for residual signal. To strengthen the fault detection technique, a residual processor is helpful in analyzing the residual signal. The residual signal is considered as a collection which containing information of fault occurrence or fault free condition. Each fault is responding to a unique condition, which determined by the pattern. When considering this kind of condition testing problem, the Shiryayev sequential probability test is useful in the residual processor design. This method bases on conditional probability of each fault, and bring a higher level of decision-making. It brings a powerful performance in residual processor.

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CHAPTER II

LITERATURE REVIEW

Fault detection and diagnosis techniques are broadly implemented in many fields for safety reason. This issue has been studied by many researchers, such as Gertler, Frank, Patton, Chen, and Ding.

The core value of fault detection is using dynamic mathematical description to build a residual generator to indicate the fault. For designing the residual generator, many studies have already proposed different techniques. Among these researches, the observer-based approach is very popular during these decades.

When fault detection system is under unknown uncertainty, the residual signal might be corrupted by these uncertainty or disturbance. For this situation, the system might have false alarm, which is oversensitive to normal signal. In order to solve this problem, decouple the disturbance from residual signal is an important task.

The complexity and sophistication of the new generation of aircrafts, automobiles, satellites, chemical plants and manufacturing lines, along with demands for higher performance, efficiency, reliability and safety, is being met by more automated control and monitoring systems.

The fault detection and diagnosis technique have been studied in many researches and applications to enhance the reliability and performance of the target systems. Venkatasubramanian and Rengaswamy published three surveys [1] - [3]. These techniques are categorized to three fields, which called quantitative methods, qualitative strategies and process history based techniques. Hwang and Kim published a survey about this field [4], and they talked about various fault detection, isolation and reconfiguration steps. The survey introduced a variety of techniques. There have been broadly studied in for decades in [1] - [5].

In quantitative model-based method, residual generation and residual evaluation are common aspect in fault diagnosis system. The system includes observer and decision logic. In the book “Model-based fault diagnosis” [6] taught about the fault diagnosis scheme, and shown several benchmark model such as inverted pendulum, bi-wheeled vehicle model, and DC motor control system. It also said that the observer-based fault detection and diagnosis technique should involves detection method and decision making tool.

Chen et al. [7] modeled a periodic system, which describes the dynamic equations of the satellite. It includes orbital mechanics and attitude dynamics. A filter is designed to diagnosis the fault of satellite. Then, the author used parity equation to depict the relationship between sensor and actuator faults. In addition, the residual process can produce probability of each type of faults by sequential probability test. This study finally integrated these four parts into a fault detection scheme, and showed the simulation result with disturbance and uncertainty.

The three-tank system was developed by Amira Gmbh, Duisburg, Germany as a real-time model about liquid transport. The system consist tanks, pumps, and pipes. It is used in chemical industry and widely studied as a benchmark of processing control or fault diagnosis technique. Ding, Jeinsch, and Zhou proposed a nonlinear controller for this system [8] and then they combined the fault detection filter together to get a fault detection scheme. A.Q. Khan and S.X. Ding further presented a fault detection filter based on h-infinity performance, and designed three kinds of threshold to make a robust fault detection scheme [9].

Wang et al. [10] proposed an active fault tolerant control scheme on three-tank model. This control scheme is combining with the neural network technique and iterative learning control module. It can be utilizing for dealing with different types of sensor faults.

Kouadri and Zelmat [11] used the discrete wavelet transform and the statistical method to propose the fault detection analysis. The procedure of detection analysis is a statistical analysis of measurement data. This method will produce a sensitive index to indicate the occurrence of faults. The author applied this study on the three-tank system.

For the analytical redundancy, it is understood as comparison between measured and observed system, and the difference is called the residual. A robust technique of residual generation should be insensitive to unknown inputs. There are various methods can achieve this goal, such as Kalman-filter, parity relation, and the Luenberger observer.

Khan et al., proposed a fault detection technique, which using closed loop fault detection techniques. This technique has several steps: the nonlinear model transformed into Lipchitz equivalent model [12], designing the fault detection filter, applying the controller [10], and utilizing different kinds of threshold. This result of this effective technique shows it ability for early fault detection and reduces the false alarm.

In this paper [9], it brought a solution about fault detection. They proposed constant and dynamic threshold in a discrete time nonlinear systems, which has process disturbances. There are different kinds of methodologies for computing the threshold to indicate the fault. A general technique is developed from signal norm. Linear matrix inequality equations derive and calculate constant threshold. For dynamic threshold, an inequality equation is derived from a nonlinear system solution. The false alarm can be eliminated successfully by using these robust thresholds.

The Luenberger observer provides an estimation of the internal state in a system, and its flexible structure is friendly to observer designer. Iqbal M., Butt Q. R., and Bhatti A. I. implemented the Luenberger observer into their research [13], and comparing the results with Li and Zhous' study, which used sliding mode observer in the three-tank system. Both of researches show advantages of the proposed fault detection strategies.

Yin S. et al [14] have a study about the data-driven observer based fault diagnosis technique. The core of this method is the identification of parity vector from measurement data. Then, designing a Luenberger- type diagnostic observer to extract the residual signal to detect the fault. After detecting the fault, the corresponding particular isolation observer will come out to in the process. The complete scheme also can implement in the three-tank system.

Duan and Patton [15] used a fault detection technique with observer-based technique in parametric approach. The Luenberger observer is operated in multivariable linear systems with disturbance. By a well parameter designing and constraining, it can decouple the unknown disturbance from residual when it is under the fault diagnosis work.

Ibaraki et al. [16] consider an algorithm for H_∞ optimization of Luenberger observer. It is a practical and intuitive method to estimation error in frequency domain. In the example of this study, this approach is successfully to design fault detection filter for the automotive passenger vehicle.

Alessandri and Coletta [17] presented an issue about designing Luenberger observer in switching discrete time linear system. In order to solve this issue, they proposed an enhance Luenberger observer by solving the linear matrix inequalities equation. It can reduce the estimation error and ensure the stability. This modified observer is utilized in simple mechanical system, and the result its effectiveness for estimation for different class discrete time linear system.

Fang et al. [18] presented a generalized observer to track the fault parameter. This full rank observer has an experimental result on three-tank system, and it can find out the location of faults fast and exactly.

Alavi and Saif [19] have a practical methodology, which is utilized on the three-tank system. In order to achieve simultaneous fault detection, they design a closed loop model and feedback control law. This methodology has a tradeoff between control system objectives and efficiency of fault detection.

The residual processing problem could be considered as a hypothesis-testing problem. It is could be solved by a statistical decision technique, which detects any change in residual signal or system parameters. The cumulative sum (CUSUM) and generalized likelihood ratio (GLR) are useful decision making tools. The sequential probability ratio test (SPRT) is also an effective algorithm. Shiryayev introduced the equation of the posterior probability for each hypothesis when based on SPRT. He also proposed an advanced research, which called multiple hypothesis shiryayev sequential ratio test (MHSSPRT). The MHSSPRT utilized a recursive algorithm and density function to compute a posteriori probability with independent measurement data. These powerful and efficient methods are all implemented in health monitoring of a satellite system [7] and detection of target maneuver onset [20].

Speyer and Whitet [21] thought that each fault could be model as a change of measurement distribution, so he believed the failure model will affect the density function.

Based on this idea, the author used the sequential probability ratio test technique and dynamic programming approach to derive a unique algorithm for fault detection. This new method is called the Shiryayev sequential probability ratio test, and it does not need a trigger test, and hence it is easy to be implemented in certain condition.

Malladi and Speyer [22] propose the multiple hypothesis shiryayev sequential probability ratio test, which is a recursive algorithm derived from his previous work, dynamic programming approach, and conditional probability test. The algorithm needs a priori probability and the probability of changing the state to calculate the a posteriori probabilities for all hypotheses. The paper showed that in certain criterion, this method is quietly sensitive and it could detect and isolate a change in independent measurement sequence.

William et al. [23] proposed a new methodology to detect a fault signal in satellite attitude control system and satellite navigation system. The fault detection filter is set for detect and isolate the tracker and gyro faults. Also, using fault mapping can help multiple shiryayev sequential probability ratio tests as a decision maker to indicate the momentum, thruster, and accelerometer faults. This study show the new methodology has its own ability to detect faults rapidly and accurately.

CHAPTER III

LUENBERGER OBSERVER

This chapter will introduce a structure of model-based residual generation, which based on perfect system model. The chapter will reintroduce general description of analytical redundancy, explain the purpose of observer, and design the framework of Luenberger observer.

The analytical redundancy is using mathematical method to reconstruct a model, which is under monitoring online. Its main idea is checking the consistency about the actual model with the reconstruct one. The difference or inconsistency between actual and reconstruct model is called the residual. The residual is computed from the observables, which includes measurement values in plants, variables of outputs, and measured inputs. When actual model differ away from ideal state, the residual becomes non-zero, and this would happened by faults. Besides, noise, disturbance, and other unknown inputs might also cause the residual vary from zero. Generating the residual is the fundamental feature of fault detection technique. In order to get the residual, which indicates the presence or absence of a fault, it is necessary to design a residual generator.

A residual generator is a crucial role in fault detection system. It main objective is creating a signal which sensitive to fault and insensitive to unknown inputs. Among a variety of techniques, the observed-based method is one of the most common ways in model-based fault diagnosis field. The observer measures the internal state of variable, and it is designed by the modern control theory and mathematical technique.

The fault detection filter is one of the observers that can generate the residual. This observer based generator was invented by Beard and Jones in 1970s. Their work strengthens the development of model-based fault diagnosis technique.

The core of fault detection filter is a state observer, which is based on the nominal system.

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x} - Du) \tag{1}$$

The residual is defined as

$$r = y - \hat{y} = y - C\hat{x} - Du \tag{2}$$

Setting a variable e, which is defined as

$$e = x - \hat{x} \tag{3}$$

Then the e yields

$$\dot{e} = (A - LC)e \tag{4}$$

$$r = Ce \tag{5}$$

When choosing L so that A-LC is stable, we can observer the r has the characteristic feature of the residual. In this situation, $\hat{x}$ gives an unbiased estimation for x. That is:

$$\lim_{t\to\infty}(x(t) - \hat{x}(t)) = 0 \tag{6}$$

From the above equations, we found the advantage of fault detection filter is that the structure is simple. For whom familiar with modern control theory, state space representation, and observer design, can utilize this observer easily. However, the fault detection filter has its own disadvantage. It requires lots of computation, because it is a full-order state observer. Other researchers tried to look for another technique, which involves reduced-order observer that contains less on-line computation.

One of the most popular residual generation techniques in model-based fault diagnosis is the diagnostic observer. The characteristic feature and core value of diagnostic observer is the Luenberger type. The reason for utilized Luenberger type observer is due to its flexible structure and clear structure. The Luenberger type observer is describing as:

$$\dot{z} = Gz + Hu + Ly \tag{7}$$

$$r = vy - wz - qu \tag{8}$$

For a system, which its state space is:

$$\dot{x} = Ax + Bu \tag{9}$$

$$y = Cx + Du \tag{10}$$

The matrices G, H, L, V, v, w, and q need to fulfill the Luenberger condition, which is described as:

1. $G \text{ is stable}$ (11)

2. $$\begin{aligned} &TA - GT = LC \\ &H = TB - LD \end{aligned} \tag{12}$$

3. $$\begin{aligned} &C = \bar{w}T + \bar{v}C \\ &\bar{q} = -\bar{v}D + D \end{aligned} \tag{13}$$

Introduce a variable e as state vector, which defined as:

$$e = Tx - z \tag{14}$$

Defined $y - \hat{y}$ as output, then according to (48) and unbiased estimation for y:

$$\lim_{t \to \infty} (y(t) - \hat{y}(t)) = 0 \tag{15}$$

then

$$\dot{e} = Ge \tag{16}$$

$$y - \hat{y} = \bar{w}e \tag{17}$$

$$r = v^* (y - \hat{y}) \tag{18}$$

Applied above equations into (8) the observer becomes:

$$\dot{z} = Gz + Hu + Ly \tag{19}$$

$$\begin{aligned} r &= vy - v\bar{w}z - v\bar{v}y - v\bar{q}u \\ &= vy - wz - qu \end{aligned} \tag{20}$$

where

$$v = v^* (I - \bar{v}) \tag{21}$$

$$w = v * \bar{w} \tag{22}$$

$$q = v * \bar{q} \tag{23}$$

Therefore, the third Luenberger condition (13) could be rewritten as follow:

$$vC - wT = 0 \tag{24}$$

$$q = vD \tag{25}$$

The next step is applied the Luenberger condition (13), (25) to get the algorithm to design the Luenberger observer.

For a nominal system, which the state space is like (9), there are four steps to complete the algorithm.

Step1: set s=3, which equal to the number of output of the three-tank system.

Step2: solving the following matrices equation.

$$v_s [\begin{matrix} C \\ CA \\ \vdots \\ CA^S \end{matrix}] = 0 \tag{26}$$

$$v_s = [\begin{matrix} v_{s,o} & v_{s,1} & \cdots & v_{s,s} \end{matrix}] \tag{27}$$

Step3: selecting g so that the G matrix is stable, which I used is [-1716 -431 -36]^T.

$$G = [\begin{matrix} G_0 & g \end{matrix}] \tag{28}$$

$$G_0 = [\begin{matrix} 0 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 1 & 0 \\ 0 & \cdots & 0 & 1 \end{matrix}] \in R^{Sx(S-1)} \tag{29}$$

$$g = \begin{bmatrix} g_1 \\ \vdots \\ g_s \end{bmatrix} \in R^S \tag{30}$$

Step4: Applying the result from last three step, and calculating L, T, H, q from the following matrices equations.

$$T = \begin{bmatrix} v_{s,1} & v_{s,2} & \cdots & v_{s,s-1} & v_{s,s} \\ v_{s,2} & \cdots & \cdots & v_{s,s} & 0 \\ \vdots & \cdots & \cdots & \vdots & \vdots \\ v_{s,s} & 0 & \cdots & \cdots & 0 \end{bmatrix} \begin{bmatrix} C \\ CA \\ \vdots \\ \vdots \\ CA^{s-2} \\ CA^{s-1} \end{bmatrix} \tag{31}$$

$$L = -\begin{bmatrix} v_{s,0} \\ v_{s,1} \\ \vdots \\ v_{s,s-1} \end{bmatrix} - g v_{s,s} \tag{32}$$

$$w = \begin{bmatrix} 0 & \cdots & 0 & 1 \end{bmatrix} \tag{33}$$

$$v = v_{s,s} \tag{34}$$

$$\begin{bmatrix} H \\ q \end{bmatrix} = \begin{bmatrix} v_{s,0} + g_1 v_{s,s} & v_{s,1} & v_{s,2} & \cdots & v_{s,s-1} & v_{s,s} \\ v_{s,1} + g_2 v_{s,s} & v_{s,2} & \cdots & \cdots & v_{s,s} & 0 \\ \vdots & \vdots & \cdots & \cdots & \vdots & \vdots \\ v_{s,s-1} + g_s v_{s,s} & v_{s,s} & 0 & \cdots & 0 & 0 \\ v_{s,s} & 0 & 0 & \cdots & 0 & 0 \end{bmatrix} \begin{bmatrix} D \\ CB \\ CAB \\ \vdots \\ CA^{s-2}B \\ CA^{s-1}B \end{bmatrix} \tag{35}$$

CHAPTER IV

SHIRYAYEV SEQUENTIAL PROBABILITY RATIO TEST

The most important characteristic of residual processor is handling the residual to find the situation of fault occurrence. It is easy to find abrupt changes in mean level of a measurement, however, some of changes will covered by noise or disturbance. Therefore, a systematic residual processor equipped with signal-processing algorithm is important. One of fault detection methods is matching incoming data with a hypothesized pattern. That is, when measuring data is coming, the algorithm runs online. Once the fault occurred, it produces an alert in minimal time.

Shiryayev sequential probability ratio test (SSPRT) is proposed by Shiryayev. It is a Bayesian approach and is based on the likelihood ratio. It is also a statistical method in signal processing. Since the fault occurrence is considered as a hypothesis, the SSPRT captures an abruptly change in hypothesis in independent measurement. The SSPRT recursive formula calculates the a posteriori probability of each hypothesis online. This algorithm is sensitive to determine the faulty situation. It provides a quick fault detection technique, which is about an abruptly change in a sequential independent measurement. We define the notation in the table 2:

Table 1. Parameters of Shiryayev sequential probability ratio test

θ_i	the time of transition to hypothesis $H_{i.}$
z_k	the measurement vector at time t_k.
Z_k	the measurement sequence up to t_k.
$f_i(x_k)$	the probability density function of x_k given hypothesis H_i.
$\tilde{p}_i$	the a priori probability of transition to hypothesis H_i from t_k to t_{k+1},

Table 1. Continued

$f_i(z)$	Probability density function of x given H_i.
$f_0(z)$	Probability density function of x given H_0.
$F_{ki}=P(\theta_i \le t_k/X_k)$	Change of distribution of measurement occurs at or before t_k.
$\pi_i = P(\theta_i \le t_0)$	The a priori probability
m	the number of hypotheses

In this paragraph, we discuss the binary hypothesis SSPRT. This algorithm is only hold one hypothesis other than null hypothesis. H_0 is defined for fault–free status, and H_1 is the fault-occurred hypothesis. There is no need to make assumption about the independent measurement sequence and mutual exclusive event. The derivation of the recursive relation for F_k, which defined as the probability that a change in the distribution occurs at or before $t_{k,}$ are shown as below:

By Bayes rule:

$$F_1 \equiv P(\theta \le t_1 / Z_1) \equiv \frac{P(z_1 / \theta \le t_1) P(\theta \le t_1)}{P(z_1)} \tag{36}$$

By definition, the conditional probability is:

$$P(z_1 / \theta \le t_1) \equiv f_1(z_1) dz_1 \tag{37}$$

Where dz_1 is an infinitesimal increment

$$\begin{aligned} P(\theta \le t_1) &= P(\theta \le t_0) + P(\theta = t_1) \\ &= P(\theta \le t_0) + P(\theta = t_1 / \theta > t_0) P(\theta > t_0) + P(\theta = t_1 / \theta \le t_0) P(\theta \le t_0) \\ &= \pi + p(1-\pi) + (0)\pi = \pi + p(1-\pi) \end{aligned} \tag{38}$$

Note that

$$\begin{aligned} P(z_1) &= P(z_1 / \theta \le t_1) P(\theta \le t_1) + P(z_1 / \theta > t_1) P(\theta > t_1) \\ &= f_1(z_1) dz_1 [\pi + p(1-\pi)] + f_0(z_1) dz_1 [(1-\pi)(1-p)] \end{aligned} \tag{39}$$

The conditional probability F_1 becomes

$$F_1 = \frac{f_1(z_1)[\pi + p(1-\pi)]}{f_1(z_1)[\pi + p(1-\pi)] + f_0(z_1)[(1-\pi)(1-p)]} \tag{40}$$

Again, by Bayes rule

$$F_2 \equiv P(\theta \le t_2 / Z_2) \equiv \frac{P(z_2 / \theta \le t_2) P(\theta \le t_2)}{P(z_2)} \tag{41}$$

Noting that

$$P(z_2 / \theta \le t_2) \equiv f_1(z_2) dz_2 \tag{42}$$

$$P(z_1 / \theta \le t_2) = P(\theta \le t_2 / z_1) P(z_1) / P(\theta \le t_2) \tag{43}$$

Then, F_2 becomes

$$F_2 = f_1(z_2) dz_2 P\theta \le t_2 / z_1) P(z_1) / P(z_2) \tag{44}$$

This can be put into a form, which similar to F_1

$$P(\theta \le t_2 / z_1) = P(\theta \le t_1 / z_1) + P(\theta = t_2 / z_1) = F_1 + p(1 - F_1) \tag{45}$$

$$P(z_2) = f_1(z_2) dz_2 [F_1 + p(1-F_1)] + f_0(z_2) dz_2 [(1-F_1)(1-p)] \tag{46}$$

Therefore, the F_2 becomes

$$F_2 = \frac{f_1(z_2)[F_1 + p(1-F_1)]}{f_1(z_2)[F_1 + p(1-F_1)] + f_0(z_2)[(1-F_1)(1-p)]} \tag{47}$$

Now, we use the result from above and add some equations to derive the multiple hypotheses SSPRT formula. In here, a null hypothesis H_0 is defined for fault-free status, and H_i is a hypothesis, which defined as each corresponding fault pattern.

$$F_{k,i} = P(\theta_i \le t_{k+1} / Z_k) \tag{48}$$

$$\begin{aligned}\phi_{ki} &= P(\theta_i \le t_{k+1} / Z_k) \\ &= F_{ki} + \tilde{p}(1 - F_{ki})\end{aligned} \tag{49}$$

Then

$$F_{1,i} = \frac{\phi_{0i} \cdot f_i(z_1)}{\sum_{i=0}^{m} \phi_{0i} \cdot f_i(z_1)} \tag{50}$$

Next

$$P(\theta_i \le t_2 / Z_2) = \frac{P(X_2 / \theta_i \le t_2) \cdot P(\theta_i \le t_2)}{P(Z_2)} \tag{51}$$

$$P(z_2 / \theta_i \le t_2) = f_1 \cdot dz_2 \tag{52}$$

$$P(z_1 / \theta_i \le t_2) = \frac{P(\theta_i \le t_2 / z_1) \cdot P(z_2)}{P(\theta_i \le t_2)} \tag{53}$$

$$P(Z_2) = P(z_2 / z_1) \cdot P(x_1) \tag{54}$$

Apply the conditional independence of the measurement sequence

$$\begin{aligned}P(\theta_i \le t_2 / z_1) &= P(\theta_i \le t_1 / z_1) + P(\theta_i = t_2 / \theta_i > t_1, z_1) \cdot P(\theta_i \le t_2 / z_1) \\ &= \phi_{1,i}\end{aligned} \tag{55}$$

$$\begin{aligned}P(z_2 / z_1) &= \sum_{i=1}^{m} P(x_2 / \theta_i \le t_2) \cdot P(\theta_i \le t_2 / z_1) + P(x_2 / \theta_0 \le t_2) \cdot P(\theta_0 \le t_2 / z_1) \\ &= \sum_{i=0}^{m} \phi_{1i} \cdot f_i(z_2) \cdot dz_2\end{aligned} \tag{56}$$

Finally, writing the recursive relation for $F_{k+1,i}$ in terms of $F_{k,i}$

$$F_{k+1,i} = \frac{\phi_{k,i} \cdot f_i(z_{k+1})}{\sum_{i=0}^{m} \phi_{k,i} \cdot f_i(z_{k+1})} \tag{57}$$

Where

$$F_{0,i} = \pi \tag{58}$$

These equations are the central role of the SSPRT and it calculates the posterior probability of each hypothesis online.

The (56), (57), and (58) equations based on Bayes rule have three assumptions. First, the measurement sequence Z_k is conditionally independent. In the fault detection problem, the measurement sequence might be time correlated.

Second, the probability density function $f_i(z)$ is assumed known in all hypotheses. However, in practice, the fault is typically unknown; it will have incomplete information about the mean of the distribution. In order to deal with this problem, we discuss one of the parameter $f_i(z)$, which denoted as α is unknown. This unknown parameter is assumed to have a distribution about itself, and then the probability density function $\psi_\alpha(x)$ defined over Ω. Therefore, the new conditional density function is written as:

$$f_1(z) = \int_\Omega f_i(x \mid \eta)\psi_\alpha(\eta)d\eta \tag{59}$$

Assume that the measurement sequence has Gaussian distribution with known variances and means under different hypotheses, and that the uniform distribution as $x \sim N(m_i, \Lambda_i)$ and $m_i \sim \mathrm{Unif}\,[b_i, b_i+2m_i]$. Hence, the conditional probability density function is written as:

$$f_i(z) = \left(\frac{1}{4^n \prod_{j=1}^{n} m_{ij}}\right)\left[erf\left\{\frac{1}{\sqrt{2}}\Lambda_i^{-1/2}(z-b_i)\right\}\right] - erf\left\{\frac{1}{\sqrt{2}}\Lambda_i^{-1/2}(z-b_i-2m_i)\right\} \tag{60}$$

where $m_i=[m_{i1}\ldots m_{in}]^T$.

For binary hypotheses, the probability density function under H_0 and H_1 are given as:

$$f_0(z_k) = f(z_k) = \frac{1}{\sqrt{2\pi\sigma}}\exp[-\frac{z_k^2}{2\sigma^2}]$$

(61)

$$f_1(z_k) = f(z_k - b) = \frac{1}{\sqrt{2\pi}\sigma}\exp[-\frac{(z_k - b)^2}{2\sigma^2}] \tag{62}$$

where b is the constant bias. In this thesis, we choose b=0.1. The σ^2 is the variance of residual signal in each fault scenario.

Third, the $\tilde{p}_i$, which is the a priori probability of transition, is assumed known for all hypotheses and constant for all stages. In this research the $\tilde{p}$ is assumed 10^{-3}. The initial condition $P(\theta_i \le t_0)$ is also assumed to be known for all hypotheses, and it is assumed 10^{-3}. Both of these are the designed parameter

CHAPTER V

THE THREE-TANK SYSTEM MODEL

In this thesis, the simulation model is the DTS200, or called the three-tank model. The three-tank model is multiple input multiple output laboratory equipment, which manufacturing by Amira Automation Company in Germany. This model has been a benchmark in process control engineering field, especially for fault detection technique, fault tolerance control, and nonlinear mathematical nonlinear controller design.

The three-tank system is consisted with three tanks, three pipelines and two pumps and the schematic description is show in the figure 1. Three identical cylinder tanks are called tank1 and tank2, which can be filled with two pumps separately, which called pump1 and pum2 individually. The liquid flow comes from pimps are denoted as Q_1 and Q_2, and flows can vary from 0 to Q_{MAX}. Both liquid flows are considered as process inputs. All of three tanks are equipped with level sensor to measure the water level in each tank, which are called h_1, h_2, and h_3, and the maximum water level is h_{max}. In this study, all of the water levels are considered as process outputs. Two circular pipes interconnect tank1 tank3 and tank2 tank3 individually, and each cross section is s_{13} and s_{23}. There is an outlet pipe, with cross section s_0, connects from tank2 to reservoir, which does not shown in this figure.

In order to get the three-tank model description, computing the dynamic model is necessary. From the conservation of liquid mass in tanks, the differential equations are obtained. The Q is denoted as flows. The A is denoted as the cross-sectional area of each tank. The details of parameters are given in the table 1.

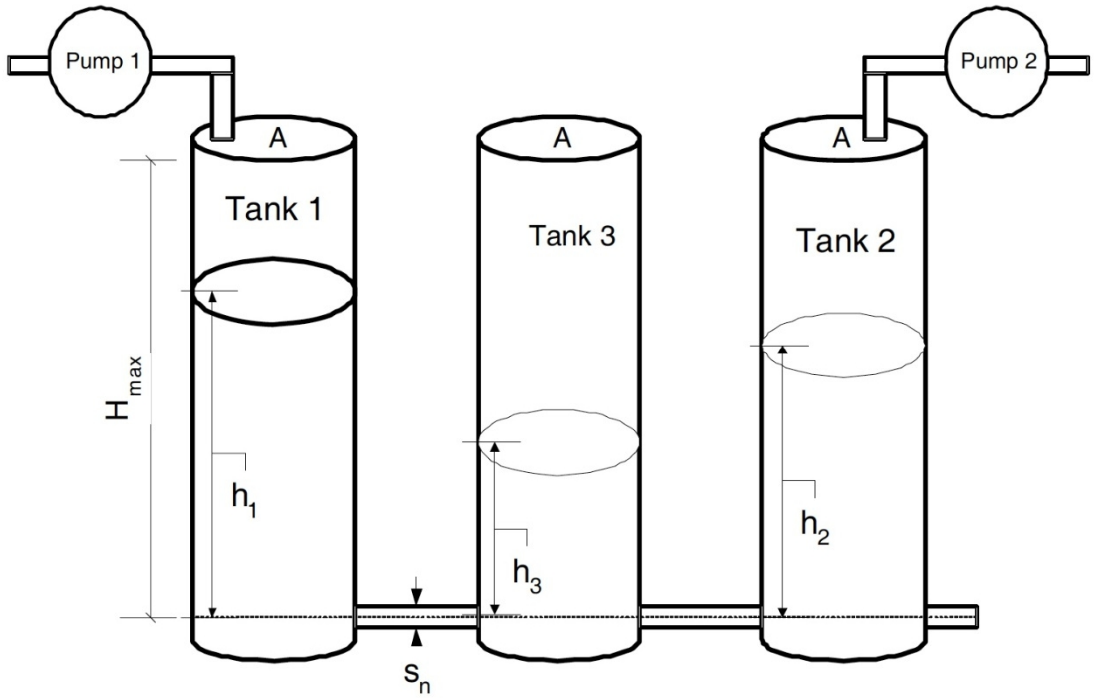

Figure 1. The schematic of three-tank system

Table 2. Parameters of the three-tank system

Parameters	Symbol	Value	Unit
Cross section area of tanks	A	154	cm^2
Cross section area of pipes	s_{12}, s_{23}, s_0	0.5	cm^2
Max. height of tanks	H_{max}	62	cm^2
Max. flow rate of pump 1	Q_{1max}	100	cm^3/sec
Max. flow rate of pump 2	Q_{2max}	100	cm^3/sec
Coeff. Of flow for pipe 1	a_1	0.46	
Coeff. Of flow for pipe 2	a_2	0.6	
Coeff. Of flow for pipe 3	a_1	0.45	

With the table above, it is necessary to using mathematical description to describe the mass flow rate by Torricelli rule. The Q_{13} represents the flow between tank 1 and tank 2 via pipe. The Q_{32} is the flow between tank 3 and tank 2. The Q_{20} is denoted as the fluid flow out from tank 2 to reservoir, which is not shown in the figure.

$$Q_{13} = a_1 s_{13} \operatorname{sgn}(h_1 - h_3)\sqrt{2g\,|\,h_1 - h_3\,|} \tag{63}$$

$$Q_{32} = a_3 s_{32} \operatorname{sgn}(h_3 - h_2)\sqrt{2g\,|\,h_3 - h_2\,|} \tag{64}$$

$$Q_{20} = a_2 s_0 \sqrt{2gh_2} \tag{65}$$

The incoming and outgoing water flow in each tank is modeled as:

$$A\dot{h}_1 = Q_1 - Q_{13} \tag{66}$$

$$A\dot{h}_2 = Q_2 + Q_{32} - Q_{20} \tag{67}$$

$$A\dot{h}_3 = Q_{13} - Q_{32} \tag{68}$$

Then, define the input and output:

$$y = x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} \tag{69}$$

$$u = \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} \tag{70}$$

In normal, the state space representation is described as:

$$\dot{x} = Ax + Bu \tag{71}$$

$$y = Cx \tag{72}$$

Apply equations into the state space representation, the model becomes as:

$$\dot{x} = \begin{bmatrix} \frac{Q_{13}}{A} \\ \frac{1}{A}(Q_{32} - Q_{20}) \\ \frac{1}{A}(Q_{13} - Q_{32}) \end{bmatrix} + \begin{bmatrix} \frac{1}{A} & 0 \\ 0 & \frac{1}{A} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} \tag{73}$$

$$y = h(x) = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{74}$$

According to sigh function and square root, this nonlinear model is not differentiable in the whole space. In order to do linearization, it is necessary separate the state space into several parts. In here, it is divided as $x_1 \leq x_3$ or $x_1 \geq x_3$, and $x_2 \leq x_3$ or $x_2 \geq x_3$.

Applying the Taylor series approximation and the equilibrium point, which h_1=45 cm, h_2=15 cm and h_3=30 cm, we get the A, B, and C matrices in state space representation:

$$A = \begin{bmatrix} -0.0085 & 0 & 0.0085 \\ 0 & -0.00195 & 0.0084 \\ 0.0085 & 0.0084 & -0.0169 \end{bmatrix} \tag{75}$$

$$B = \begin{bmatrix} 0.0065 & 0 \\ 0 & 0.0065 \\ 0 & 0 \end{bmatrix} \tag{76}$$

$$C = I_{3x3} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{77}$$

In reality, the environmental surrounding disturbances or unexpected change interfere the system signal in the process plant or controller. These interferences that might influence the system performance are called unknown input. There are two kinds of unknown input: the load disturbance and measurement noise. The load disturbance d is an input that leads the system away from the desired performance, and also distorted the process variable x. The measurement noise n would corrupt the measurement signal y. We integrate these unknown inputs into state space, and then the model becomes:

$$\dot{x} = Ax + Bu + E_d d \tag{78}$$

$$y = Cx + Du + F_n n \tag{79}$$

The E_d and F_n are constant matrices. The d and n are unknown input vector with zero mean and variance Σ_v, and it is denoted as $d \in \mathcal{N}(0, \Sigma\nu)$ and$n \in \mathcal{N}(0, \Sigma\nu)$.

The fault is a symptom that generally abnormal deviate away from a normal status or acceptable range of calculated parameters and observed state variables in a process. The fault would be defined as process abnormality such as unusual water level or low system performance. The underlying causes about an abnormality are called the root cause or basic event. One of root cause might cause by constant sensor bias or a scaling failure. Some of facilities provide feedback signal from control plant, which is essential and enhance the purpose of diagnostic system. The other one is structural changes. Due to hard failure in equipment such as stuck valves, broken pipe, and poor pump performance, it alters the process.

Sensor offset and scaling in the measurement drive the sensor fault, which directly act on the process measurement. The scaling is varied from 0% to 100%, which means from totally healthy to complete failure. The offset value is in between 0 and h_{max}. The mathematical representation of sensor fault is:

Sensor fault = scaling * measurement of the corresponding sensor + sensor offset.

These faults are denoted as f_1, f_2, and f_3.

Something unusual happens and causes changes or interference in the actuator would lead to the actuator fault. In the three-tank system, it represents the abnormal pumps performance, and then pumps make the fluid volume shifts dramatically. The scaling of actuators can vary from 0%, which means zero water flow, to 100%, which means the pump open its maximum performance. The mathematical representation of actuator fault is:

Actuator fault = scaling * flow rate in pump

The faults are expressed as f_4 and f_5.

Leakage faults are one of the process faults. The fault is indicating a malfunction within the process plant. The fault is caused by the broken pipe or valve failure and so on. The leaks are modeled as $\theta_{A_1}\sqrt{2gh_1}$, $\theta_{A_2}\sqrt{2gh_2}$, $\theta_{A_3}\sqrt{2gh_3}$; where the θ is a parameter and depends on the leak size. These faults are represented by f_6, f_7 and f_8.

We combine these three fault descriptions into the state space mentioned in previous paragraph, which it contains the unknown input. Then, the new state space representation becomes:

$$\dot{x} = Ax + Bu + E_d d + E_f f \tag{80}$$

$$y = Cx + Du + F_n n + F_f f \tag{81}$$

The E_f and F_f are constant matrices. The f is a matrix, which contains sensor, actuator, and leakages fault mathematic description.

The three-tank model is a nonlinear function. In control theory, we need to find the linear approximation. For a dynamic system, linearization is a technique that gets the local stability at equilibrium point. This technique is often used in engineering, economics and physics field.

For the linearization, it is necessary separate into several regions, which are x1>=x3 or x1<=x3 and x2>=x3 or x2<=x3. Plug the equilibrium points into Taylor series approximation, which is about x_{10}=45cm, x_{20}=15cm, and x_{30}=30cm. Also, there is an assumption, which is x_{10}≠x20≠x30.

After linearization at operating point h_1=45cm, h_2=15cm and h_3=30cm. In Taylor series expansion, we have to ignore the higher order terms. We have the following linear model:

$$\dot{x} = Ax + Bu + E_d d + E_f f \tag{82}$$

$$y = Cx + Du + F_n n + F_f f \tag{82-1}$$

$$x = y = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} \tag{83}$$

$$u = \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} \tag{84}$$

$$A = \begin{bmatrix} -0.0085 & 0 & 0.0085 \\ 0 & -0.00195 & 0.0084 \\ 0.0085 & 0.0084 & -0.0169 \end{bmatrix} \tag{85}$$

$$B = \begin{bmatrix} 0.0065 & 0 \\ 0 & 0.0065 \\ 0 & 0 \end{bmatrix} \tag{86}$$

$$C = E_d = F_n = I_3 \tag{87}$$

$$D = 0 \tag{88}$$

$$E_f = \begin{bmatrix} 0 & I_{3x5} \end{bmatrix} \tag{89}$$

$$F_f = \begin{bmatrix} I_3 & 0_{3x5} \end{bmatrix} \tag{90}$$

$$f = \begin{bmatrix} f_1 & f_2 & f_3 & f_4 & f_5 & f_6 & f_7 & f_8 \end{bmatrix}^T \tag{91}$$

$$d = \begin{bmatrix} d_1 & d_2 & d_3 \end{bmatrix}^T \tag{92}$$

$$n = \begin{bmatrix} n_1 & n_2 & n_3 \end{bmatrix}^T \tag{93}$$

The controller is reference form [10], which decoupled the three-tank system into two nonlinear first order subsystems. The controller is described as:

$$u_1 = Q_1 = Q_{13} + A(a_{11}h_1 + v_1(w_1 - h_1)) \tag{94}$$

$$u_2 = Q_2 = Q_{20} - Q_{32} + A(a_{22}h_2 + v_2(w_2 - h_2)) \tag{95}$$

Where $a_{11} \leq 0$ and $a_{22} \leq 0$, and we choose $a_{11}=0$, $a_{22}=0$. The v_1 and v_2 represent two pre-filters, which we choose $v_1=v_2=0.05$. The w_1, w_2 are reference signals, which we choose 0.45 and 0.15. The nominal closed loop model is:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} (a_{11} - v_1)x_1 \\ (a_{22} - v_2)x_2 \\ \dfrac{a_1 s_{13} \operatorname{sgn}(x_1 - x_3)\sqrt{2g \mid x_1 - x_3 \mid} - a_3 s_{23} \operatorname{sgn}(x_3 - x_2)\sqrt{2g \mid x_3 - x_2 \mid}}{A} \end{bmatrix} + \begin{bmatrix} v_1 & 0 \\ 0 & v_2 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \tag{96}$$

CHAPTER VI

SIMULATION RESULTS

The figure 2 shows the healthy condition of the three-tank system. In the beginning the actuator1 and the actuator2 opened its maximum performance, so that the water level in each tank went up quickly. When around 300 seconds, all of tanks reached its desired water level, and both actuators also had steady inlet speed. The system went into steady state condition after 300 seconds. The rest of simulation will be demonstrated after 300 seconds.

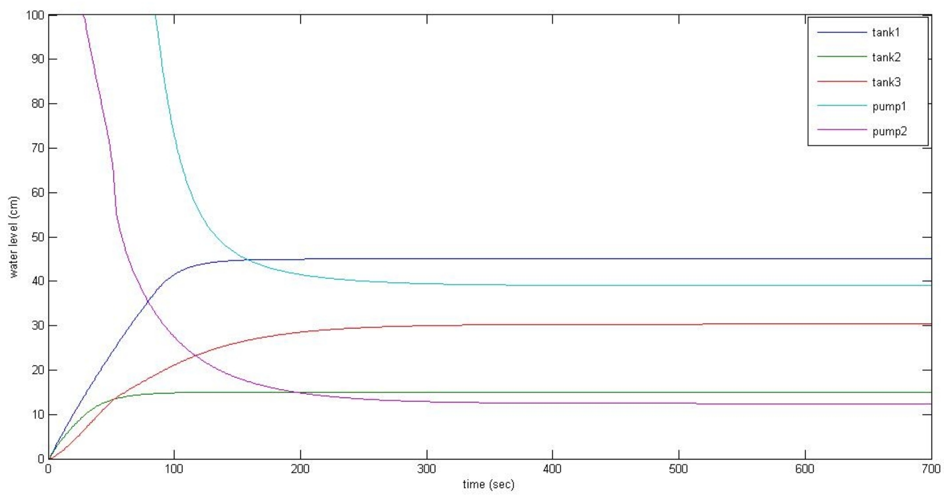

Figure 2. The healthy condition of the three-tank system

Based on the Simulink model, the noise and disturbance are added in one channel separately and the value is shown in the table3. The one percent noise or disturbance means that it would cause root mean square of fluctuation of water level in tank 1 is one present of original water level in tank 1.

Table 3. The values of noise and disturbance

	Noise	Disturbance
1%	N (0 , $8x10^{-6}$)	N (0 , $3x10^{-9}$)
2%	N (0 , $2x10^{-5}$)	N (0 , $9x10^{-9}$)
3%	N (0 , $1.1x10^{-4}$)	N (0 , $2.2x10^{-8}$)

The three-tank system in healthy condition with one, two and five percent noise and disturbance are showed in the figure 3, figure 4, and figure 5.

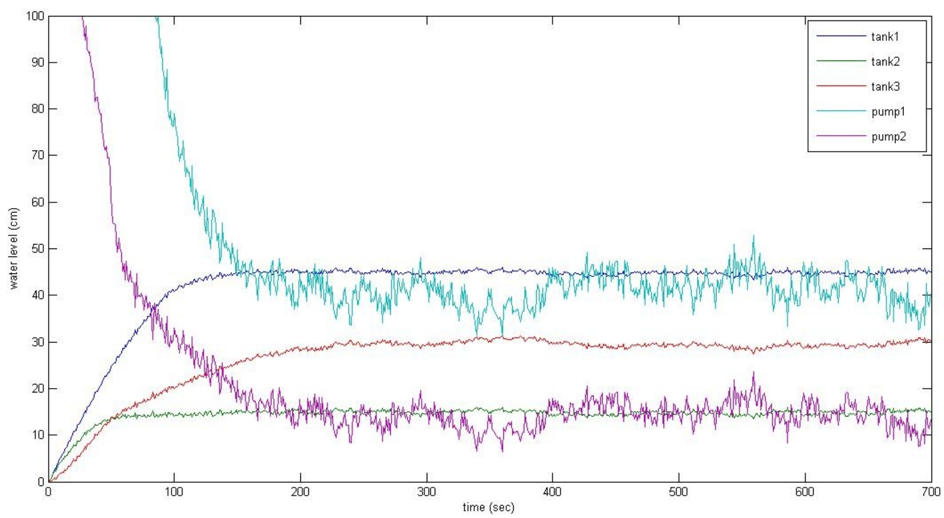

Figure 3. The healthy performance with one percent noise and disturbance

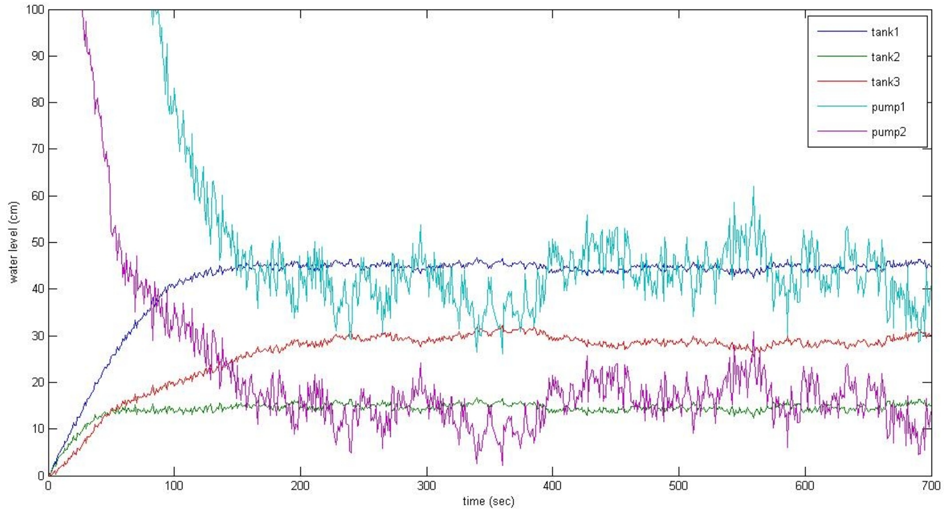

Figure 4. The healthy performance with two percent noise and disturbance

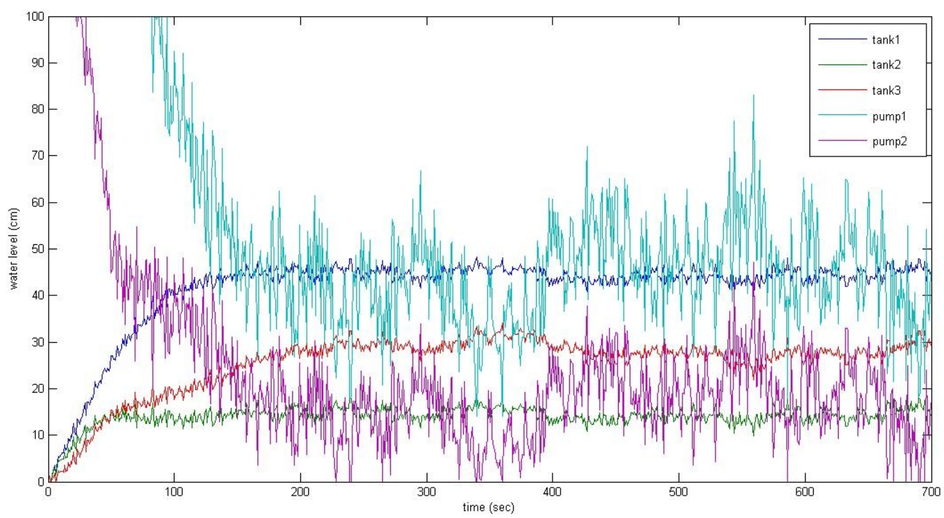

Figure 5. The healthy performance with five percent noise and disturbance

This section will demonstrate the sensor fault, which acted on tank 1 with different percentage of noise and disturbance. The first scenario is sensor fault happened between 350 to 400 seconds. As we can observe in the figure 6, the water level of tank 1 has abnormal shift from 45 cm to nearly 80 cm at 350 seconds, and actuator 1 shut down at the same time. The reason of shut down is that the three-tanks system found the water level of tank 1 was over high, so the system close actuator 1.

The level went down gradually from 350 seconds and actuator 1 still closed. But this figure 6 only reflected the sensor measurement not the real water level. In reality, water level in tank 1 was fall down, because the tank 1 had no inlet water and the rest of water flew to the tank 3. That is, it had been bellowed the desire level since 350 seconds. At 400 seconds, the sensor went back to normal performance, and it detected the water level of tank 1 is far below the normal level. So the figure of sensor measurement of tank 1 showed there is a dropped at this time. When system found the water level was below than normal one, the actuator 1 opened to maximum again. Then, the actuator 1 went down gradually until the water level of tank 1 back to its desired position.

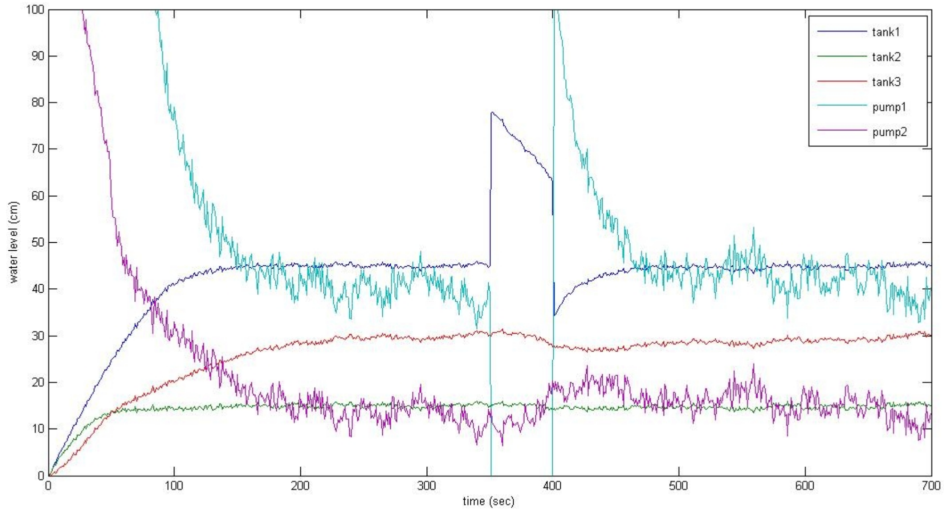

Figure 6. The sensor fault with one percent noise and disturbance

When measured variable and state variable caught by the Luenberger observer, the observer processed its algorithm to produce the residual signal, and the result is shown in the figure 7. The residual in the beginning of rose up due to every measured variable are far away from desired value. After 300 seconds, the residual signal went into the steady state condition. The residual rose up quickly, when sensor fault occurred. As we can observe, this Luenberger observer can capture the time when sensor fault occurred.

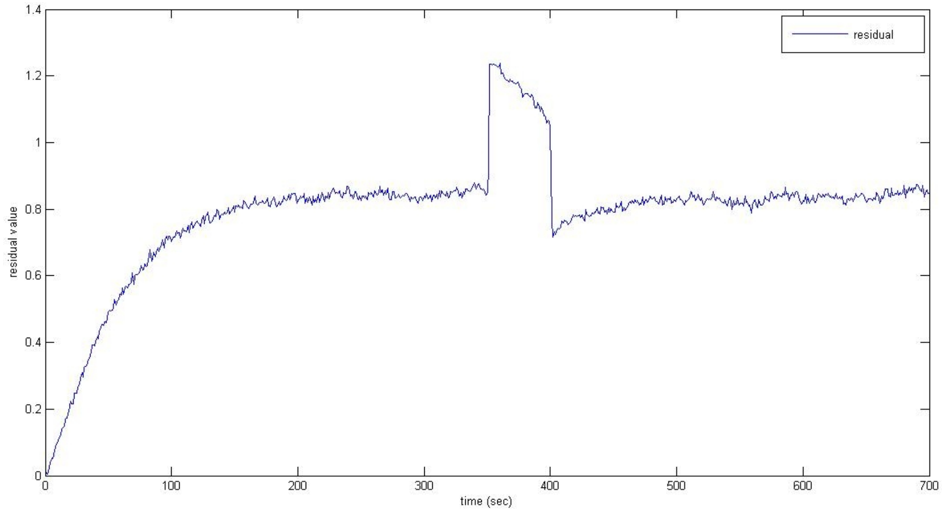

Figure 7. The residual signal of sensor fault with one percent noise disturbance

The residual processor used the residual signal from residual generator with the Shiryayev sequential probability ratio test algorithm to calculate the a posteriori probability to indicate the fault occurrence. From the figure 8, the residual process can detect the time when sensor fault occurred successfully.

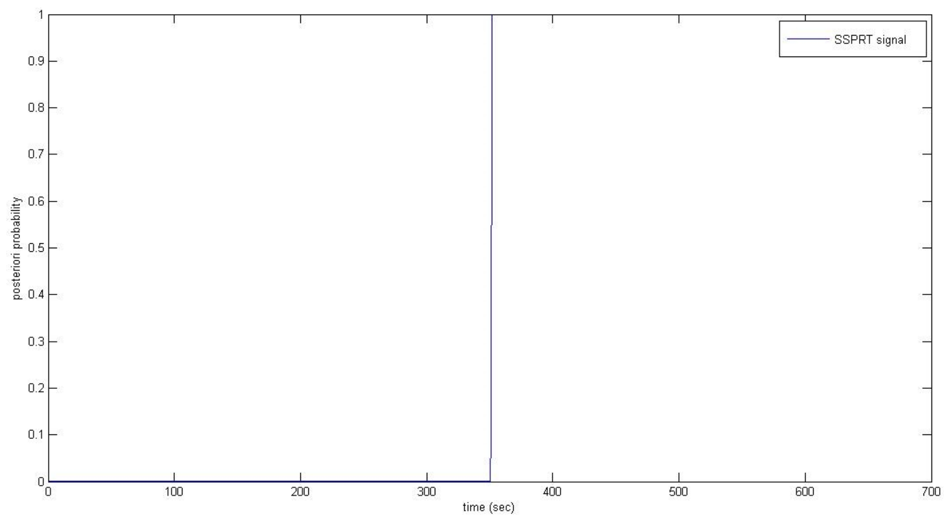

Figure 8. The SSPRT result of the sensor fault with one percent noise disturbance

The next simulation is the sensor fault on tank 1 with two percent noise and disturbance. This figure 9 is the performance of three-tank model in actuator fault. The time of fault occurred is among 350 to 400 seconds.

For the residual signal, the result in the figure 10 is similar to the simulation of one percent noise and disturbance. The observer can show the fault presence interval clearly. For the result from residual processor in the figure 11 even though there was a small tremble signal before 350 seconds, the residual processor still pointed out the time of the fault occurred successfully.

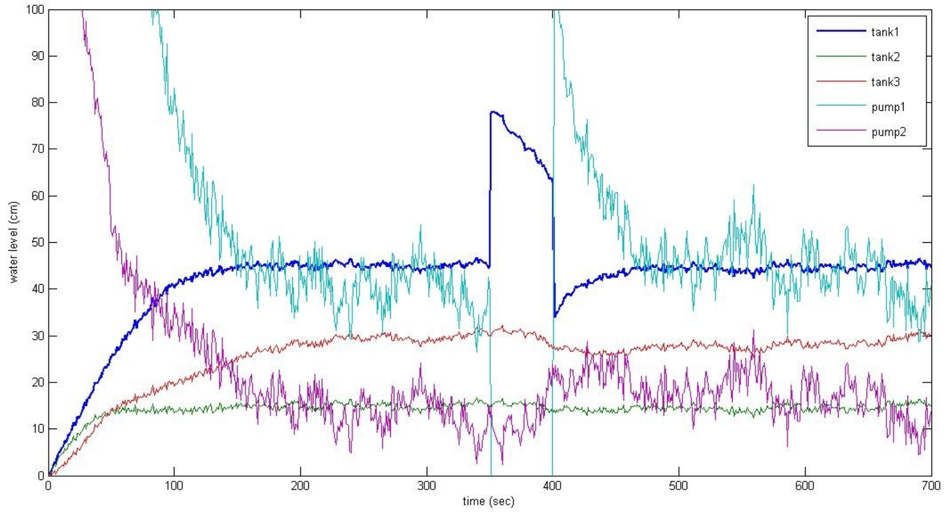

Figure 9. The sensor fault with two percent noise and disturbance

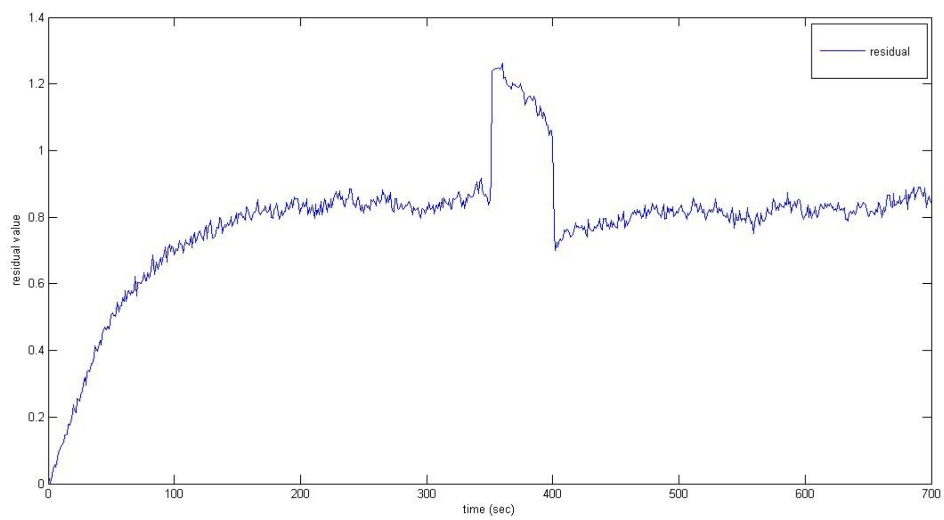

Figure 10. The residual signal of sensor fault with two percent noise and disturbance.

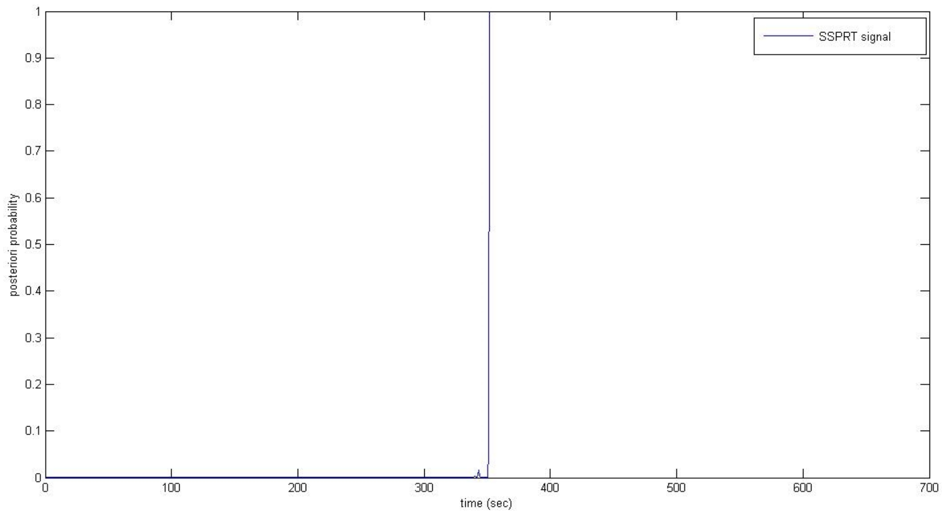

Figure 11. The SSPRT result of the sensor fault with two percent noise disturbance.

The last subset of sensor fault scenario is integrated with five percent noise and disturbance. The results are very similar to previous simulation. Both Luenberger observer can signalize the time period of fault occurred and the Shiryayev sequential probability ratio test can detect the fault effectively. The result is shown in the figure 12, the figure 13, and the figure 14.

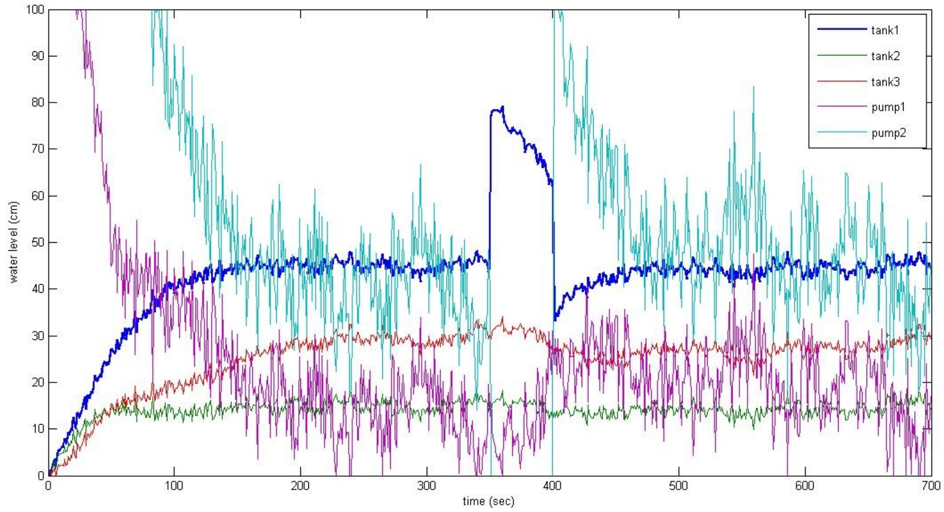

Figure 12. The sensor fault with five percent noise and disturbance

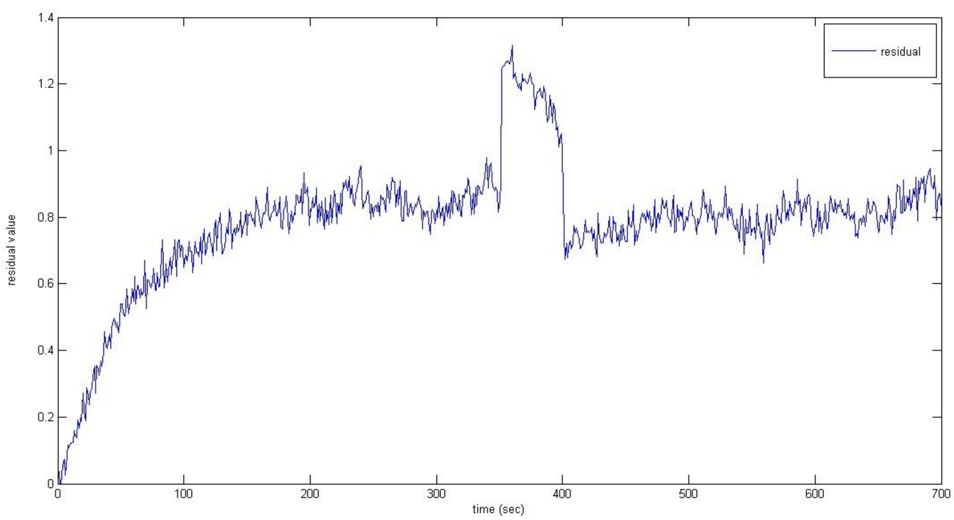

Figure 13. The residual signal of sensor fault with five percent noise and disturbance

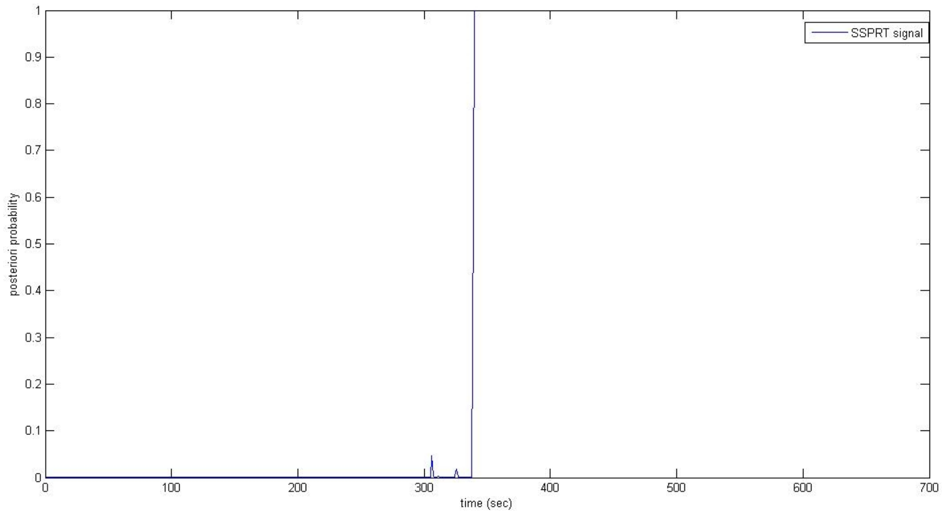

Figure 14. The SSPRT result of the sensor fault with five percent noise and disturbance

The leakage is happened when the tank has a hole that the water flows out from the tank, so that the water level will drop very quickly. This is one of our fault detection scenarios. This figure 15 is the leakage fault with one percent noise and disturbance. We can notice that the water level in tank 1 was decent very quickly, and the tank 2 was also been influenced.

The actuator 1 opened its maximum performance when the three-tank system found the water level in tank 1 was below than normal situation. Also, the actuator 2 increases its inlet water to compensate the water in tank 2. Tank 1 and tank 2 had filled to desired level gradually since 400 seconds.

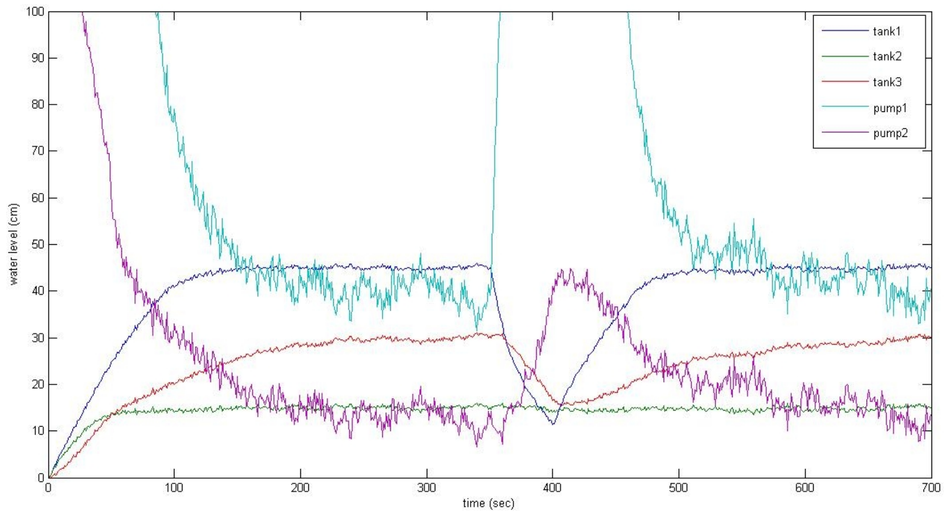

Figure 15. The leakage fault with one percent noise and disturbance

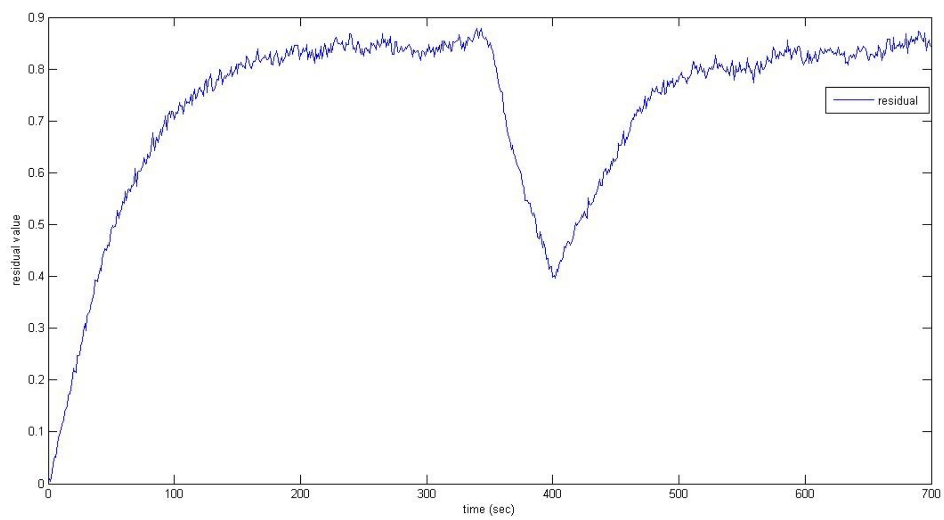

Figure 16. The residual signal of leakage fault with one percent noise and disturbance

The figure 16 presents the residual signal had a big v-shape to show this kind of abnormal situation.

Because of the easy-observed residual signal, the residual processor pointed out the time when fault occurred easily. The result is shown in the figure 17.

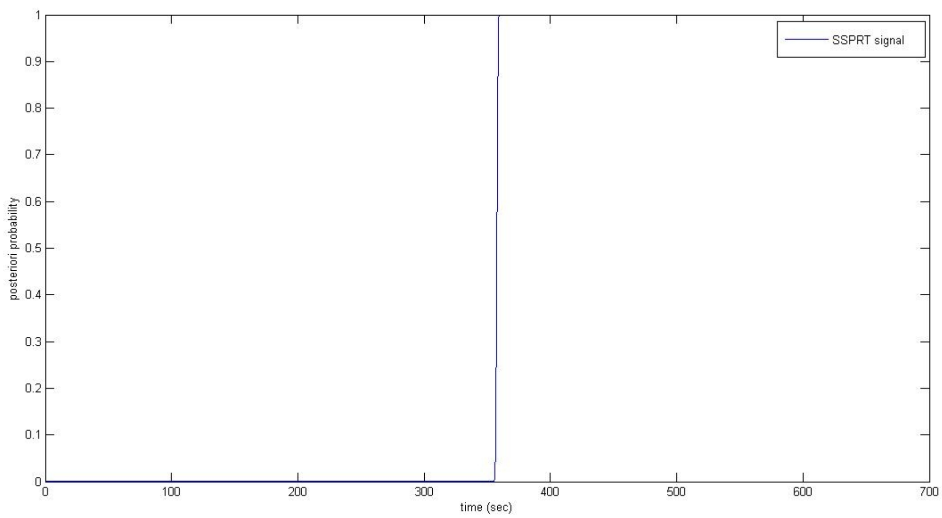

Figure 17. The SSPRT result of the leakage fault with one percent noise and disturbance

The figure 18 is the leakage fault with two percent noise and disturbance was shown in following figures. The water level dropped quickly, and both actuators increased their inlet water into tank 1 and tank3.

The figure 19 is the residual signal, which was quite the same with previous experiment. We can find out the fault occurrence both in residual signal or the other signal from the residual processor in the figure 20.

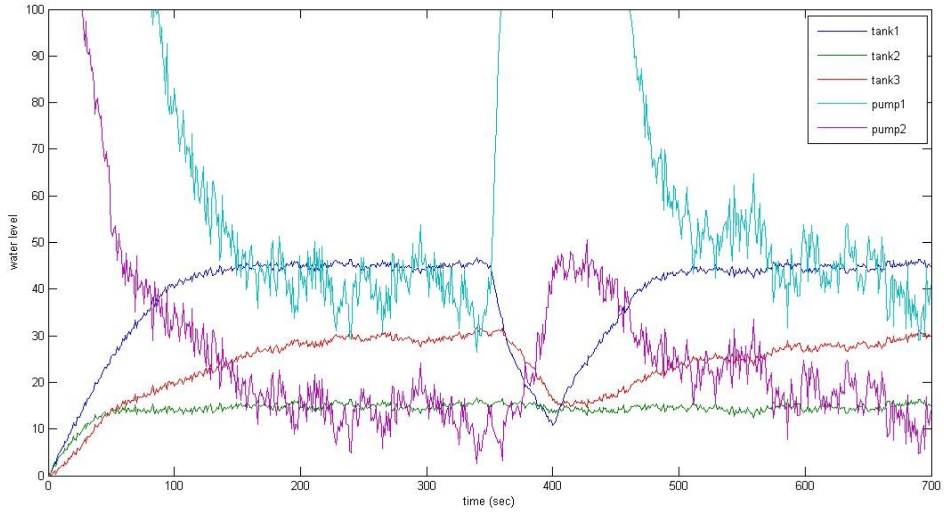

Figure 18. The leakage fault with two percent noise and disturbance

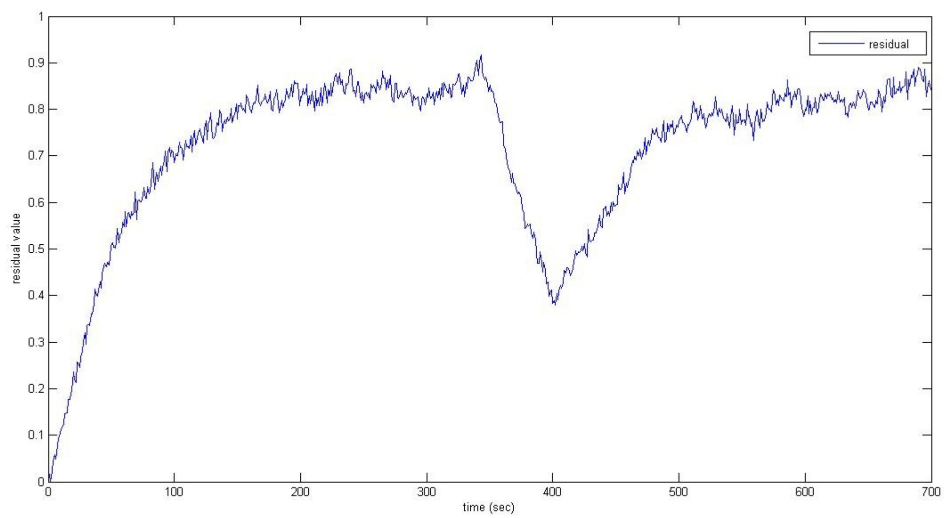

Figure 19. The residual signal of leakage fault with two percent noise and disturbance

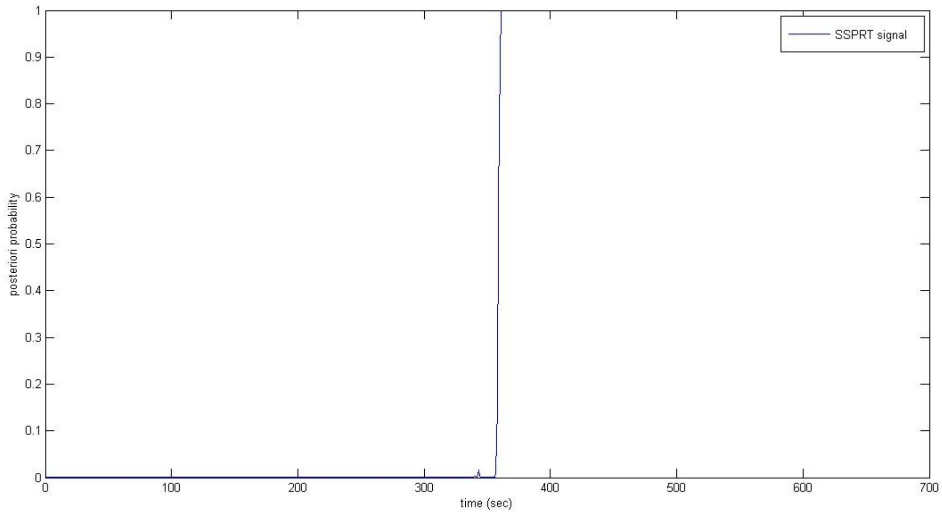

Figure 20. The SSPRT result of the leakage fault with two percent noise and disturbance

The experiment of leakage fault with five percent noise and disturbance will be explained in this paragraph, the figure 21. With five percent noise and disturbance, we can see that every line in the figure was oscillated very much. The water level and performance of actuators were very similar with the previous two experiments. That is, it is obvious that the water in tank 1 and tank 2 ran out quickly, and the pumps had high performance about inlet water into tank 1 and tank 2.

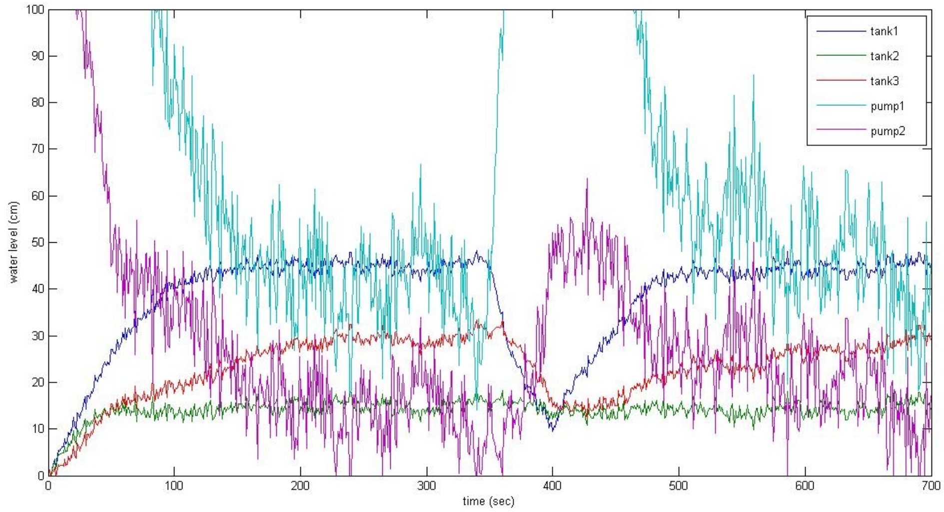

Figure 21. The leakage fault with five percent noise and disturbance

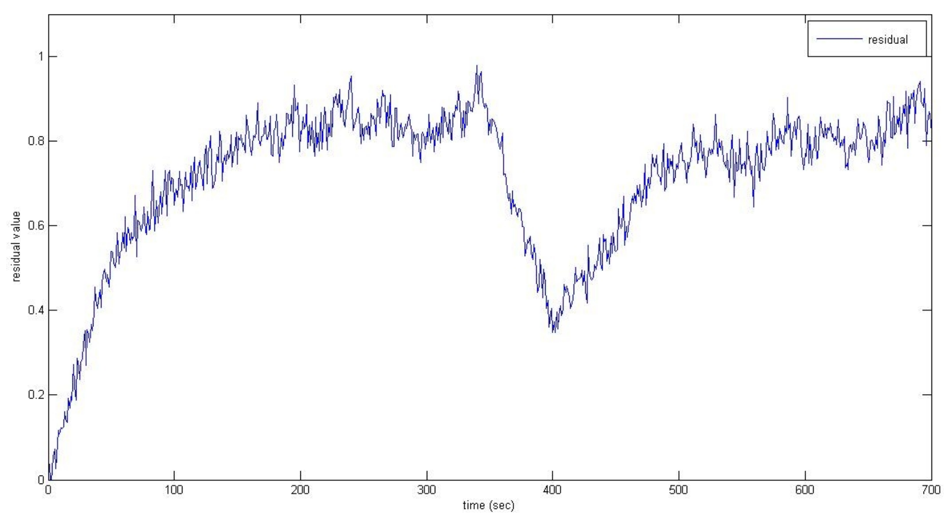

Figure 22. The residual signal of leakage fault with five percent noise and disturbance

The residual signal in the figure 22 had a big drop between 350 seconds and 450 seconds. So in this time interval, there might have a fault in the three-tank system.

The Shiryayev sequential probability ratio test was utilized for residual processor and the result is the figure 23. With the residual signal from residual generator, which used the Luenberger observer, it dealt with signal that can indicate the time of fault occurrence. The signal had a peak at 350 seconds. Then after ten to twenty seconds, the signal rise from zero to one, which means that the residual processor pointed out this time the leakage fault was presented.

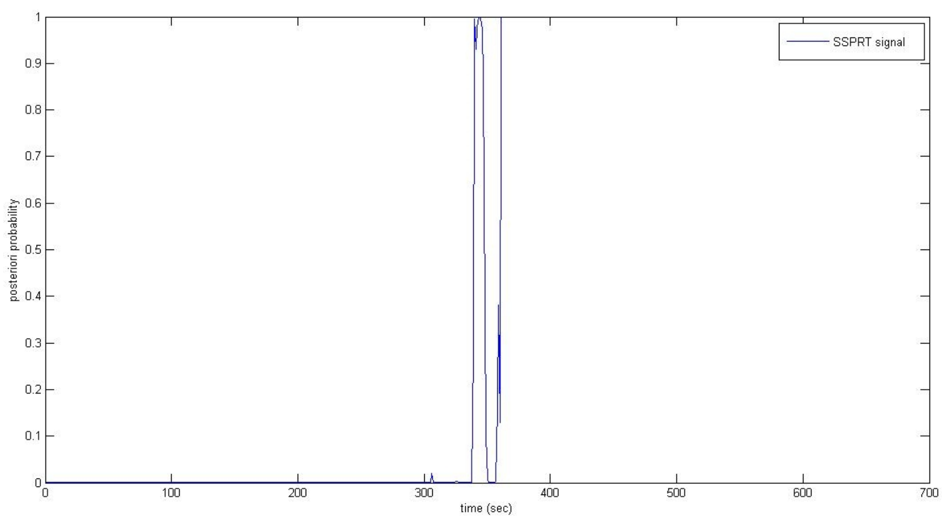

Figure 23. The SSPRT result of the leakage fault with five percent noise and disturbance

The time of actuator occurred was also happened at 350 to 400 seconds, and the system performance is shown in the figure 24. I set the actuator 1 had abnormal high performance in my reconstruct model in MATLAB. In this research, the fault was only happened in the reconstruct model, not in the reality three-tank system. For real three-tank system, it received a signal, which said the actuator 1 had over high performance from reconstruct model. So the actuator in real three-tank system declined its inlet water. Because of descending of inlet water, the water level in tank 1 also went down.

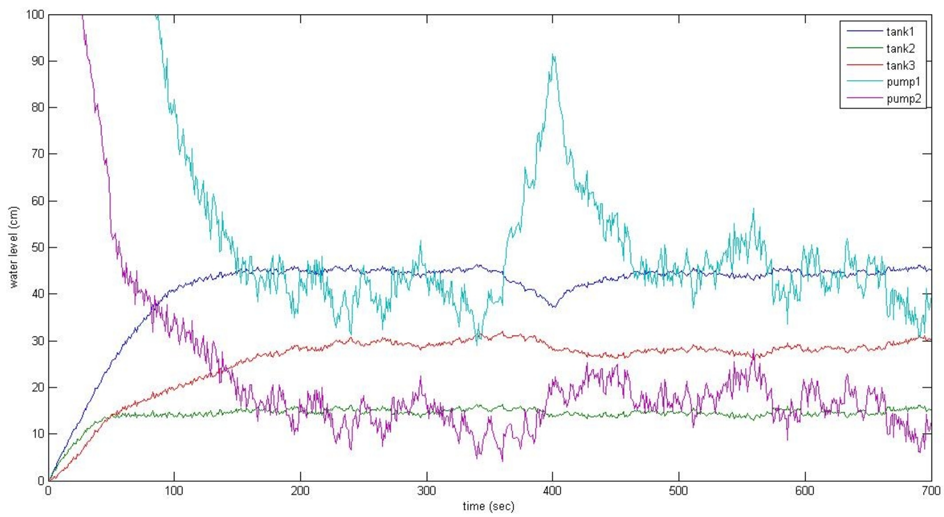

Figure 24. The actuator fault with one percent noise and disturbance

This figure 25 is generated from the residual generator. The signal had dropped a little from 350 seconds. Even though the dropped signal is not oblivious than sensor fault scenario, we can have reason to doubt there was a fault occurred during this time period.

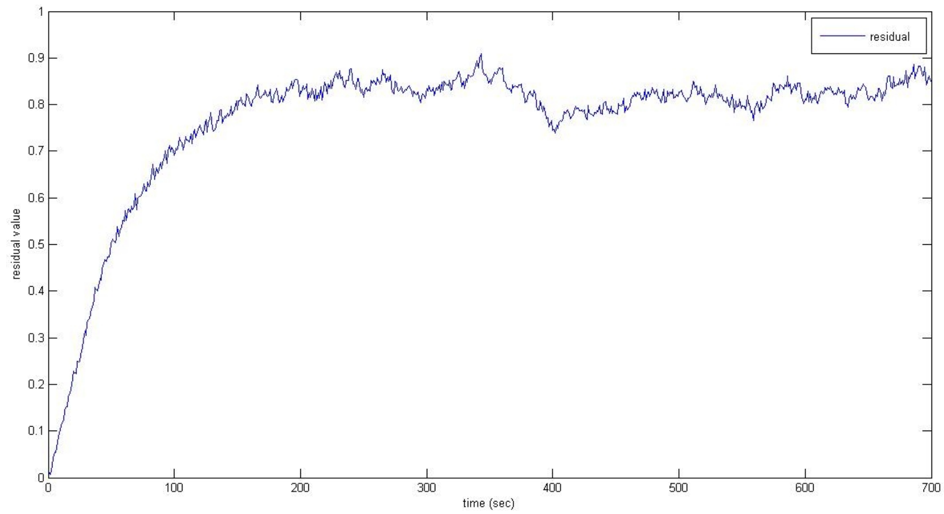

Figure 25. The residual signal of actuator fault with one percent noise and disturbance

Next the residual processor, which applied Shiryayev sequential probability ratio test, used the residual signal to indicate the fault. The result is the figure 26. Even though there is a little bit time delay, the residual processor can figure out the fault successfully.

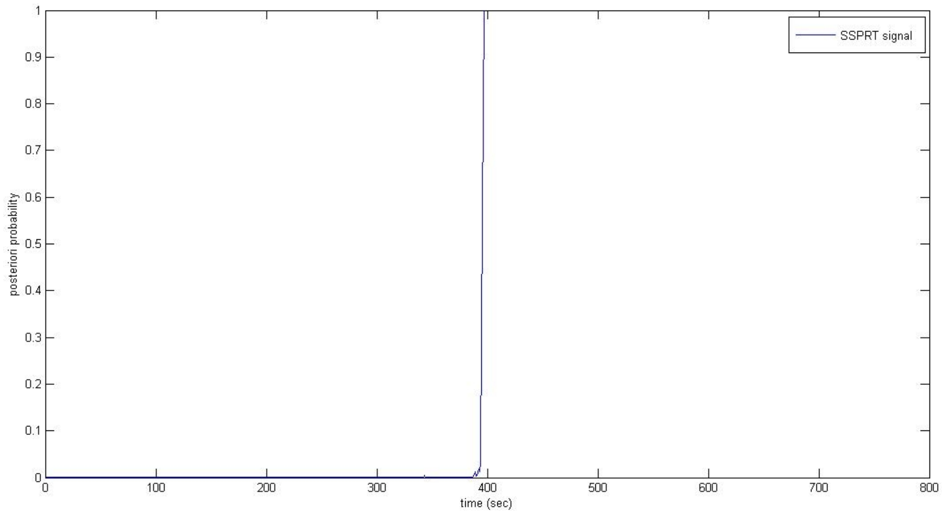

Figure 26. The SSPRT result of the actuator fault with one percent noise and disturbance

The result of actuator fault with two percent noise and disturbance are described in this paragraph. The figure 27, which describes the actuator performance, is similar with one percent noise and disturbance test. However, we can observe that the line in this figure is more vibrated than previous one. And the next figure is the water level in each tank.

The figure 28 of residual signal cannot show the fault signal very clearly. We only can observer that the residual signal went down a little bit at 350 seconds, and it cannot represent the occurrence of fault.

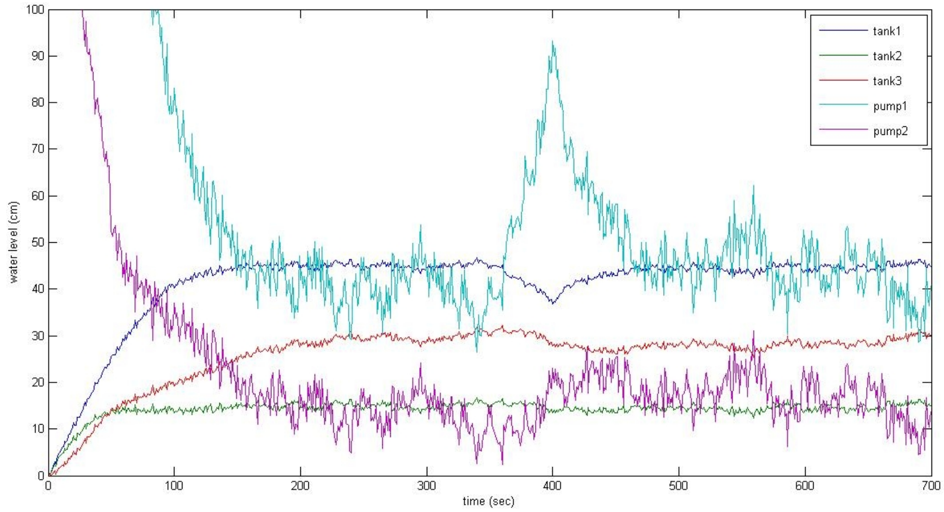

Figure 27. The actuator fault with two percent noise and disturbance

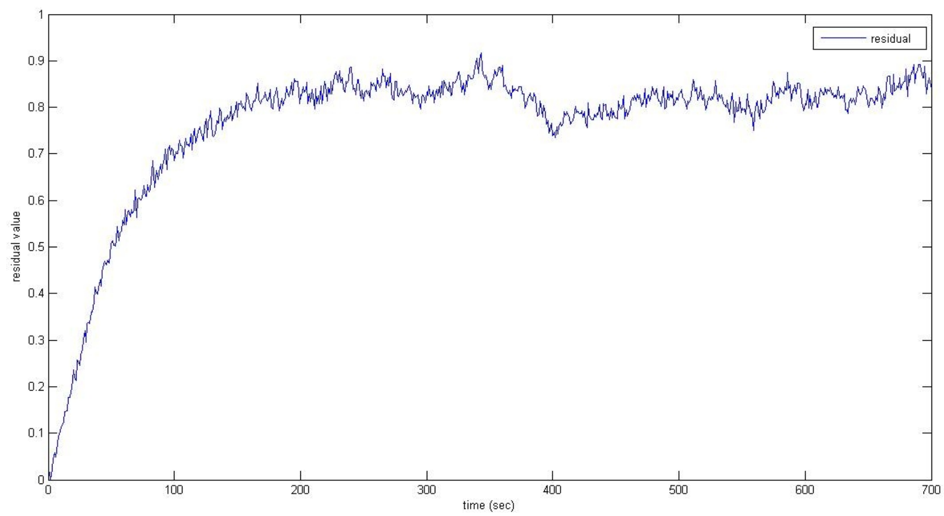

Figure 28. The residual signal of actuator fault with two percent noise and disturbance

The residual processor consumed the residual signal and shows its powerful performance in the figure 29. There was a little peak before 400 seconds, and then the signal went up near 400 seconds. So the residual processor can detect the fault with some time delay.

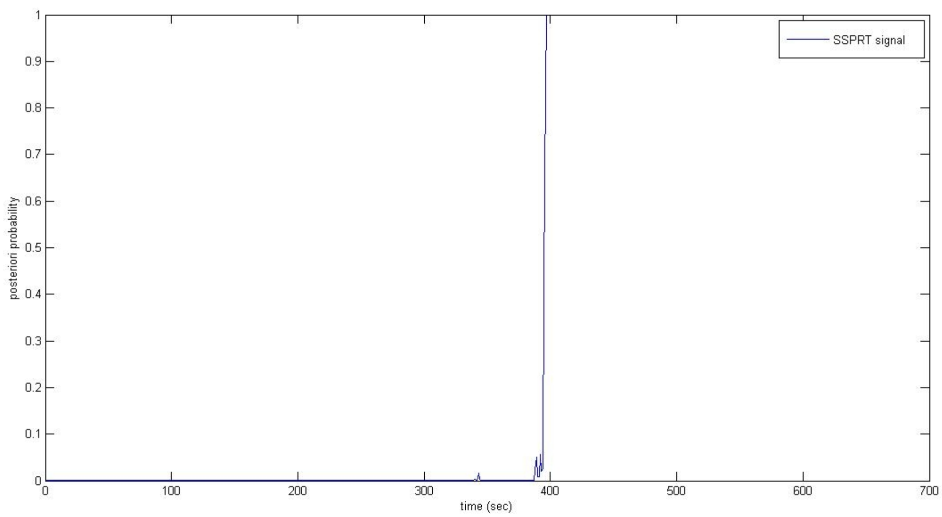

Figure 29. The SSPRT result of the actuator fault with two percent noise and disturbance

The experiment of actuator fault with five percent noise and disturbance had similar result in the figure 30. The performances of actuator are fluctuating a lot, and the tank 1 had the water level drop between 350 and 400 seconds.

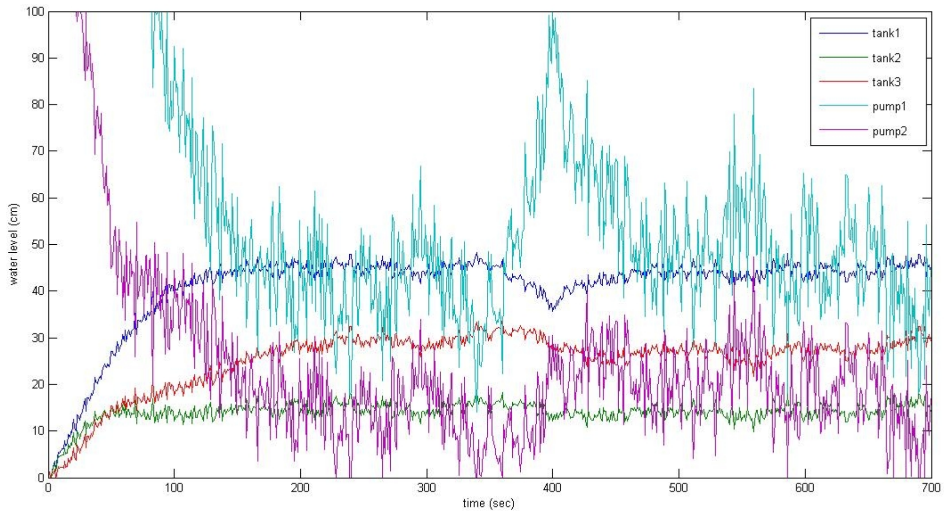

Figure 30. The actuator fault with five percent noise and disturbance

In this situation, the residual signal barely showed obvious trend about the fault in the figure 31. So we need to rely on the residual processor to eliminate the unnecessary information, which hide in the residual signal.

The signal created by residual signal showed its strength in the figure 32. At 350 seconds the signal fluctuated a lot, and the fluctuation was caused by noise and disturbance in system, and the result algorithm calculation. When time was near 400 seconds, the signal can indicate the occurrence of the actuator fault.

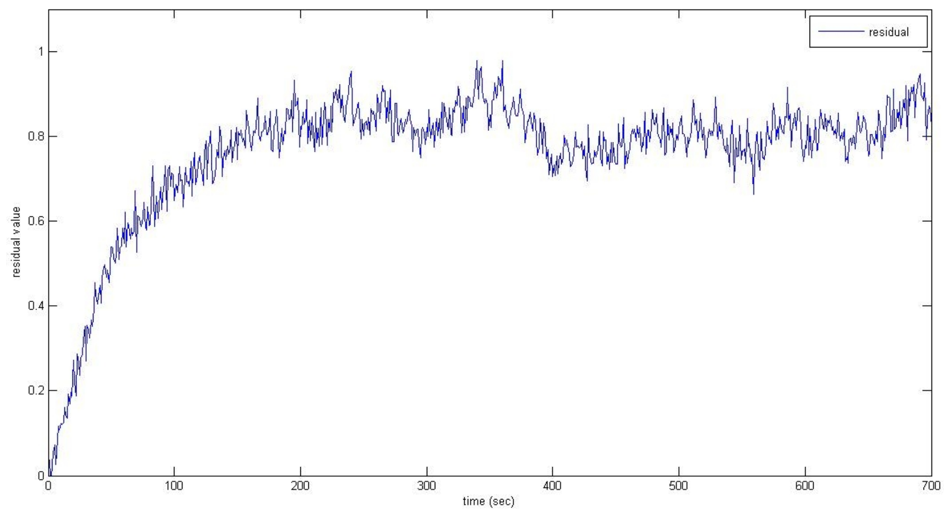

Figure 31. The residual signal of actuator fault with five percent noise and disturbance

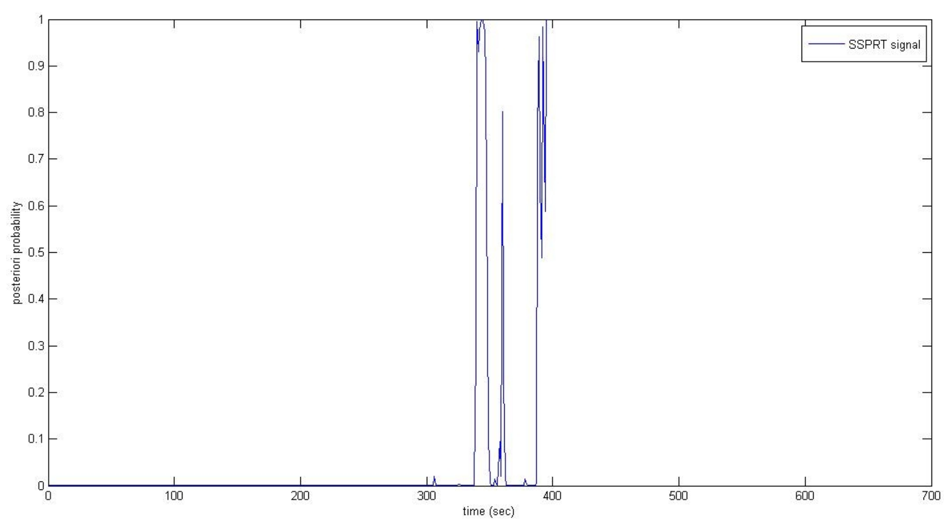

Figure 32. The SSPRT result of the actuator fault with five percent noise and disturbance

CHAPTER VII

SUMMARY

The research of the model-based fault diagnosis on three-tank system is based on analytical redundancy. The fault diagnosis system consist the Luenberger observer as the residual observer, and Shiryayev sequential probability ratio test as the residual processor. The performance of this fault diagnosis system is evaluated by MATLAB simulation for the presence of faults, noise, and disturbance. The results from experiments show the effectiveness of model-based fault diagnosis system.

For sensor faults, the residual generator produces clear residual signal, and the residual processor indicated the time of fault occurrence timely. For the leakage faults, the residual signal has a deep V-shape in the period of fault occurred, and the residual processor indicates the fault occurred successfully. When the noise and disturbance becomes bigger, the residual processor has a little time delay. For the actuator faults, the residual generator cannot create a meaningful residual signal during the period of actuator fault presence. However, the signal from Shiryayev sequential probability ratio test still sensitive enough that it announces the time of fault occurrence with some time delay and has some oscillation before the announcement. The increasing of signal-to-noise ratio results in detection time delay and signal oscillation

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